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Assessing Tractors' Active Safety in Serbia: A Driving Simulator Study

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Abstract

The active safety of tractors remains a major concern in rural road environments, where tractor drivers face high crash risks due to limited vehicle visibility. In Serbia, 1.4% of crashes involve tractors, mainly due to poor visibility (64.3%), lack of beacon lights, unsafe overtaking, and unmarked stopped tractors (14.3% each). These issues reduce safety, increase fuel consumption and emissions, and cause economic losses. A driving simulator study with 117 drivers examined how visibility equipment affects speed perception. The results showed that 20 km/h was best estimated with all visibility aids, while 10 km/h was most accurately judged with only the slow-moving vehicle emblem. These findings emphasize the potential for simple, cost-effective visibility measures to enhance the active safety of tractors in mixed rural traffic conditions. By enhancing tractor visibility, these measures reduce crash risks, minimize unnecessary acceleration and deceleration, and lower fuel consumption and emissions associated with traffic disturbances. Furthermore, by preventing crashes, these solutions contribute to reducing resource consumption in crash-related medical care, vehicle repairs, and infrastructure damage. Integrating improved visibility equipment into rural traffic policy can significantly enhance tractors' active safety and reduce the risk of crashes in agricultural regions.

Keywords: tractor visibility; speed perception; driving simulator; active safety; sustainability

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1. Introduction

Modern sustainable transportation requires not only the reduction of emissions and energy consumption [1,2] but also effective management of traffic safety, particularly the active safety of slow-moving vehicles, such as tractors, in rural traffic environments [3,4]. In Serbia, tractors are involved in approximately 1.4% of all road crashes [5], often with severe consequences due to limited vehicle visibility. Contributing factors include poor lighting, lack of standardized warning signs, and unsafe overtaking practices. As the presence of agricultural machinery on public roads increases, evaluating and improving their active safety becomes essential for preventing collisions and protecting all road users.

Despite the widespread recognition of visibility-related risks, there is limited empirical research examining how specific visibility aids, such as daytime running lights (DRLs), beacon lights, and the slow-moving vehicle (SMV) emblem, affect drivers' perceptual accuracy. Most previous studies have focused on passenger vehicles and motorcycles, leaving a knowledge gap concerning tractors, particularly under real-world conditions simulated through driving environments. Given the unique operational characteristics and vulnerability of tractors, this gap represents a critical limitation in advancing evidence-based improvements in their active safety. This study seeks to bridge this research gap by systematically evaluating the influence of various visibility equipment configurations on drivers' speed perception of tractors within a controlled driving simulator environment. By focusing on perceptual accuracy as a key determinant of safe interaction with tractors, the study directly contributes to the assessment of their active safety in rural traffic contexts.

The remainder of this paper is structured as follows: Section 2 provides a review of relevant literature on vehicle visibility and speed perception. Section 3 details the experimental design, including participant characteristics and simulation conditions. Section 4 presents the results of the statistical analysis. Section 5 discusses the implications of the findings, and Section 6 concludes with a summary and recommendations for future research.

2. Literature Review

Sustainable transportation research increasingly recognizes the need to integrate traffic safety considerations into broader environmental and socio-economic frameworks. Within this context, vehicle visibility, particularly for vulnerable road users, such as agricultural machinery, plays a dual role: it enhances safety and contributes to the efficiency and resilience of transport systems. The subsequent subsection examines the integration of vehicle visibility measures within the broader framework of sustainable transportation, prior to delineating their empirically established contributions to traffic safety and driver perception research.

2.1. The Role of Vehicle Visibility in the Context of Sustainable Transportation

While the enhancement of vehicle visibility is primarily viewed through the lens of traffic safety, its broader implications for sustainable transportation are increasingly recognized. Sustainable transportation encompasses more than environmental efficiency, it also integrates social and economic dimensions, such as the reduction of traffic injuries, optimization of energy use, and minimization of infrastructure strain [6–8]. From this perspective, improved vehicle visibility, particularly for vulnerable and slow-moving vehicles, such as tractors, can be seen as a critical factor contributing to long-term sustainability goals.

Firstly, increasing the visibility of agricultural vehicles has a direct impact on reducing crash frequency and severity. Fewer road crashes translate into lower demand for emergency services, medical treatment, vehicle repair, and road infrastructure maintenance, all of which consume substantial resources and generate emissions [9,10]. It has been estimated that road traffic crashes contribute to national carbon footprints, both through direct emissions (e.g., vehicle leaks, fire, fuel loss) and indirect impacts, such as road reconstruction and hospital energy use [11–13]. Moreover, the deployment of driving simulators for research, as used in this study, supports sustainability by eliminating the need for physical vehicle testing [14]. Real-world experiments typically involve the use of fuel, road space, and controlled environments, each of which bears environmental costs. In contrast, simulators offer a reproducible, low-emission, and resource-efficient alternative for studying driver behavior, perception, and safety-related variables [15,16].

However, visibility-enhancing technologies themselves, particularly DRLs, warrant a nuanced consideration. While DRLs improve perceptual conspicuity and reduce crash risk, they also contribute to marginally increased fuel consumption and CO_2 emissions, especially in conventional internal combustion engine vehicles. Estimates suggest that

DRLs can increase fuel use by approximately 0.3–1.5%, depending on the technology employed (e.g., halogen vs. LED) [17,18]. Nonetheless, these environmental costs are typically offset by the broader societal benefits of crash reduction, especially when modern energy-efficient lighting systems, such as LED DRLs, are utilized [19,20]. Furthermore, the economic costs of road crashes in agricultural areas are disproportionately high when considering the limited transport infrastructure and availability of emergency response services. Visibility interventions that help reduce such incidents thus support economic resilience in rural areas [21–23]. In summary, vehicle visibility measures, especially those targeting high-risk vehicle types, like tractors, should be considered not only as safety improvements but also as integral components of a sustainable transportation framework.

2.2. Vehicle Visibility Equipment and Perceptual Factors in Traffic Safety

The role of visibility-enhancing equipment, such as daytime running lights (DRLs), beacon lights, and slow-moving vehicle (SMV) emblems, in improving road safety remains insufficiently explored. These devices are primarily intended to support timely and effective interactions between road users, acting as a fundamental element for maintaining safe and predictable traffic flow [19,24–26].

Between 2019 and 2021 in Serbia, a total of 99 fatal road crashes and 704 injury-related crashes involved tractors. These incidents resulted in 101 fatalities and 1079 injuries. On average, approximately 34 individuals lose their lives and 360 are injured each year in tractor-related crashes. Tractors are involved in about 1.4% of all road crashes, yet they account for roughly 6.5% of total fatalities and about 2% of all injuries in traffic accidents in Serbia [27–30].

A study by Marković et al. [31] further highlights the nature of these crashes, noting that 33.4% of collisions with tractors occur at the rear-left or front-left sections of the vehicle. In the case of tractors towing trailers, as many as 58.6% of collisions involve the rear-left section of the trailer (Figure 1). These patterns are most often linked to overtaking maneuvers under nighttime conditions, where poor visibility makes it difficult for other road users to perceive the tractor in time to avoid a collision [32–37].

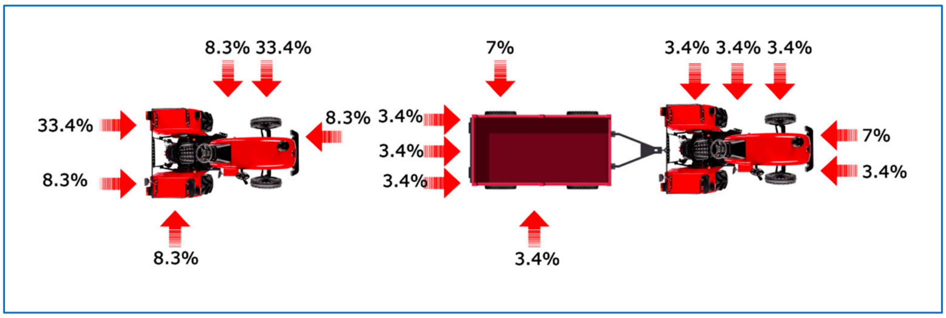

Figure 1. Representation of damage on a tractor and a tractor with a trailer in road crashes [31].

Marković et al. [31] emphasize that a predominant share of road crashes involving tractors—up to 64.3%—can be attributed to insufficient visibility of the vehicle. Specific contributing factors include the absence or malfunctioning of beacon lights, as well as unsafe overtaking practices and the failure to mark stationary tractors or trailers, each accounting for 14.3% of such incidents. An additional 7.1% of cases involve undetermined or ambiguous causes, often due to limitations in post-crash investigation data.

These findings reinforce the crucial role of vehicle visibility in accident prevention. Road safety improvements largely depend on drivers' perceptual abilities, including early detection of an approaching vehicle, accurate estimation of its speed, and correct assessment of the time required to perform a safe maneuver, such as overtaking or yielding [19,37–40].

Theories of visual perception, such as the illumination contrast theory, further underline that a vehicle's visibility is strongly influenced by its luminance contrast with the background environment [40]. In response to such insights, most developed countries have mandated the use of daytime running lights (DRLs) across all vehicle categories as a cost-effective means of increasing vehicle conspicuity and enhancing traffic safety [19,28,41,42]. In Serbia, by contrast, current legislation requires only the use of a yellow beacon light on tractors and the display of the "slow-moving vehicle (SMV) emblem" as warning indicators [29].

Empirical research supports the effectiveness of DRLs in improving traffic safety outcomes. According to aggregated data, passenger vehicles equipped with DRLs show a 24.6% reduction in fatalities, a 20% reduction in injuries, and a 12.4% decrease in the frequency of multi-vehicle crashes during daytime conditions [19,43]. Historical findings corroborate this impact, with a 1996 study reporting that cars with DRLs were involved in 10–15% fewer multi-vehicle collisions than those without them [44].

Beyond safety statistics, DRLs also influence drivers' perceptual judgments. Several studies have demonstrated that the presence or absence of DRLs significantly affects the accuracy of vehicle speed estimation [19,24,43]. For instance, Pešić et al. [24] revealed that drivers consistently misjudge the speed of oncoming vehicles depending on whether DRLs are turned on or off. These discrepancies become particularly pronounced at higher speed ranges, notably 70 and 90 km/h. The authors concluded that DRLs significantly improve perceptual accuracy on roads with higher speed limits, thereby potentially reducing the likelihood of high-speed overtaking errors [32,45–47]. Similarly, Ivanišević et al. [19] found a statistically significant difference in the perception of motorcycle speed depending on the DRL configuration—whether turned off, turned on, or using an advanced LED DRL system. Their results indicated that speed estimation errors are substantially lower when motorcycles are equipped with LED DRLs, especially at higher speeds (70 and 90 km/h), across both urban and rural road environments. These findings suggest that DRLs—particularly those using LED technology—play a crucial role in enhancing a vehicle's perceptibility and aiding drivers in making accurate perceptual judgments at various speed limits [48–51].

While much of the existing research has focused on passenger vehicles and motorcycles, little is known about the perceptual implications of visibility equipment for tractors. The specific effect of DRLs, beacon lights, and the SMV emblem on the estimation of tractor speed has not yet been systematically investigated [52–54]. This gap in the literature highlights the need for further study, particularly considering the distinct operating speeds and physical characteristics of tractors. To address this gap, the present research aims to explore how different combinations of visibility equipment influence the accuracy of drivers' speed estimation for tractors. By simulating various visibility scenarios using a driving simulator, this study seeks to identify which equipment configurations contribute most effectively to perceptual clarity and improved road safety outcomes.

To provide context for the present research, Table 1 summarizes several key studies that have examined the impact of daytime running lights and vehicle visibility on speed perception and traffic safety. These studies highlight diverse methodological approaches and consistently underscore the role of visibility equipment in enhancing perceptual accuracy and reducing crash risks.

Table 1. Summary of selected studies on vehicle visibility and speed perception.

Authors and Year	Title	Methodology	Key Findings
Pešić et al. (2019) [24]	Evaluation of the effects of daytime running lights for passenger cars	Driving simulator experiment; comparison of DRL on/off conditions	DRLs significantly improve speed estimation accuracy, especially at higher speeds (70–90 km/h)
Ivanišević et al. (2022) [19]	The impact of daytime running (LED) lights on motorcycles speed estimation	Driving simulator; assessment of motorcycle speed with and without LED DRLs	LED DRLs enhance speed perception accuracy at higher speeds on both urban and rural roads
Cavallo & Pinto (2012) [25]	Are car daytime running lights detrimental to motorcycle conspicuity?	Laboratory-based experimental study	DRLs on cars can reduce motorcycle visibility, especially when both vehicles use DRLs
Peña-García et al. (2010) [26]	Influence of daytime running lamps on visual reaction time of pedestrians	Psychophysical tests with pedestrians in controlled environments	DRLs shorten pedestrian reaction time when detecting vehicle turn signals
Elvik (1996) [44]	A meta-analysis of studies concerning the safety effects of daytime running lights on cars	Meta-analysis of multiple studies	DRLs reduce fatalities by ~25%, injuries by ~20%, and daytime crashes by ~12%
Koornstra et al. (1997) [43]	The Safety Effects of Daytime Running Lights	Analytical study using international data	DRLs improve safety, particularly in frontal and side collisions

3. Materials and Methods

For the purposes of this paper, an experiment was carried out on a driving simulator, with the aim of examining the differences in the estimation of the tractor's speed, in situations where the tractor's daytime running lights, beacon lights, and a "slow-moving vehicle (SMV) emblem" were installed.

3.1. Experimental Design Overview

For the purposes of this experiment, the test subjects were presented with 12 different conditions of tractor movement on the driving simulator: 2 conditions when a "slow-moving vehicle (SMV) emblem" was installed on the tractor, 2 conditions when the tractor's daytime running lights were on, 2 conditions when the tractor had the beacon light on, 2 conditions when the beacon light was on AND a "slow-moving vehicle (SMV) emblem" was installed, 2 conditions when the daytime light was on and a beacon light and "slow-moving vehicle (SMV) emblem" were installed, as well as 2 conditions when there was no equipment on the tractor. The tractor moved at speeds of 10 and 20 km/h in all conditions.

The driving simulator was used to simulate traffic on a two-lane, undivided road during a sunny day for the participants [24]. The study focused on analyzing the characteristics of the trajectory during free-flow driving, without any roadside interruptions. The simulation environment included typical traffic signs and vegetation, but no additional objects were introduced in the traffic scenes to prevent influencing the participants' expectations about the movement of the visual targets, as well as avoiding any potential distractions [19,24,55].

In the experiment, the participants were tasked with estimating the speed of a tractor approaching them under all the conditions described above [19]. The participants provided their estimates orally, while an assistant entered the spoken values into the appropriate field of an online questionnaire [19,32,45,55–59]. The questionnaire also included questions about demographic characteristics (gender and age), place of residence, level of education, possession of a driving license (including the category of license held and the number of years the participant had held it), frequency of tractor driving, frequency of driving, and participation in road crashes [19,24,55].

3.2. Stimuli and Experimental Conditions

In this study, the tractor was selected as a representative example of slow-moving agricultural vehicles that frequently operate on rural roads and interact with faster traffic streams. While tractors, as slow-moving vehicles in rural areas, are an important subject of active safety analysis, they constitute a critical component of rural mobility systems, especially in countries with strong agricultural sectors. Improving the active safety of such vehicles supports multiple sustainability goals, including injury prevention and resource conservation.

For this study, a 3D model of the "IMT" tractor, model "539" in a red color, was utilized. The tractor's dimensions are 2972 mm in length and 1800 mm in width, and it has a wheelbase of 1830 mm. This model was selected due to its widespread use in agricultural regions of Southeast Europe, ensuring ecological and practical relevance. Two tractor speeds (10 km/h and 20 km/h), were selected for the experiment, reflecting typical real-world operational conditions for tractors on public roads [47].

The visibility equipment selected for this experiment reflects legally required and commonly implemented configurations for agricultural vehicles. The DRL (manufacturer Hella GmbH & Co. KGaA, Lippstadt, Germany) used was a standardized halogen-based daytime running light, designed to provide excellent visibility for the tractor in daylight. In this configuration, the tractor's primary headlight is represented using halogen lighting [24,54].

A "slow-moving vehicle (SMV) emblem" (Figure 2) was placed on the front side of the tractor, while the beacon light (Figure 3) was placed on the rear side of the tractor. The rotating amber beacon light, designed to alert surrounding traffic of slow or obstructive movement, was placed at the highest structural point of the vehicle to maximize visibility. This selection of equipment allowed for systematic testing of six visibility configurations, enabling the evaluation of both isolated and combined effects on driver perception.

Figure 2. Slow-moving vehicle (SMV) emblem.

Figure 3. Beacon light.

3.3. Driving Simulator Setup

Driving simulators are widely recognized as effective tools for studying perceptual and cognitive aspects of driving behavior, especially in situations that would be difficult or unsafe to replicate in real-world conditions [19,24,55].

The driving simulator is equipped with three 42-inch plasma screens (Panasonic TH-42PWD6 plasma screen, manufacturer Panasonic Corporation, Osaka, Japan.), providing participants with a 180° horizontal and 50° vertical field of view of the simulated environment. Each screen has a resolution of 1360 × 768 pixels and a refresh rate of 60 Hz [24,55]. Research has shown that a minimum horizontal field of view of 120° is essential for accurate speed perception [55]. The simulation environment was designed to replicate a two-lane undivided rural road under sunny daylight conditions, incorporating standard road signs and natural roadside vegetation. No additional vehicles or environmental distractions were introduced to ensure experimental control and focus on the target vehicle. Along with visual stimuli, participants received spatially consistent ambient traffic sounds, enhancing immersion and realism. Before beginning the trials, each participant received a standardized briefing and a practice run to familiarize themselves with the equipment and procedures.

3.4. Experimental Protocol

The study was carried out in the Republic of Serbia during October and November 2022. Participants did not receive any form of compensation for their involvement in the research [55]. Each participant was assessed individually and underwent preliminary trials [55]. At the start of the experiment, every participant was assigned a unique sequence of experimental stimuli, determined using a random number generator [19]. This approach aimed to mitigate the anchoring effect by implementing counterbalancing, achieved by randomizing the sequence in which the test stimuli were presented [24]. Respondents were asked to estimate the tractor's speed under 12 distinct visibility conditions: (1) with only the SMV emblem installed, (2) with daytime running lights (DRLs) activated, (3) with a beacon light activated, (4) with both the beacon light and SMV emblem, (5) with the full set of visibility equipment (DRLs, beacon light, and SMV emblem), and (6) with no visibility equipment installed. Each of these six configurations was presented at two different speeds (10 km/h and 20 km/h), resulting in a total of 12 experimental scenarios. Participants observed each scenario within the driving simulator and verbally reported their speed estimates, which were recorded by an assistant. No predefined response options were offered, ensuring open-ended and unbiased input.

3.5. Data Collection and Statistical Processing

The data were gathered through an online questionnaire and subsequently imported into the MS Excel software package, Office 2019 (Microsoft Corporation, Redmond, WA, USA) [60–62]. After importing, the data were thoroughly reviewed and validated [55]. Statistical analysis of the collected data was then performed using IBM SPSS Statistics version 22.0 (IBM Corp., Armonk, NY, USA) [33,63–66]. The normality of the distribution was assessed by examining histograms and performing the Kolmogorov–Smirnov test. Since the distribution of data for all measured variables was found to be normal, parametric methods were applied. To evaluate the significance of differences, the independent samples *t*-test, one sample test, and one-way ANOVA were utilized [24,67–70].

The null hypothesis (H_0) stated that there is no statistically significant difference in tractor speed perceptions. The alternative hypothesis (Ha) is that there are statistically significant differences in tractor speed perceptions.

The statistical significance threshold (α) was set at 5%. Therefore, if the probability (p) is less than or equal to 0.05, the null hypothesis (H_0) is rejected, and the alternative hypothesis (H_a) is accepted. Conversely, if p is greater than 0.05, H_0 is not rejected.

The DRL is a specialized daytime running light designed to provide excellent visibility for the tractor in daylight. In this configuration, the tractor's primary headlight is represented using halogen lighting [24,55]. A "slow-moving vehicle (SMV) emblem" was placed on the front side of the tractor, while the beacon light was placed on the most prominent point of the tractor.

4. Results

4.1. Demographic Data

A total of 117 respondents participated in the study [38,39], with an average age of 28.2 years. The youngest respondent was 17 years old (X_{min}), and the oldest was 55 years old (X_{max}). The sample consisted of 57.3% male respondents and 42.7% female respondents. The highest percentage of respondents, 41.9%, completed high school, followed by 18.8% who completed basic professional studies, 15.4% completed basic academic studies, and 11.1% of respondents completed master's academic studies. Additionally, 12.8% of respondents completed vocational secondary education or other forms of non-academic training. 41.4% of the respondents reported living in rural areas, 44% in urban areas, 10.3% in suburban areas, and 4.3% in small towns. Many respondents, 72.6%, hold a driver's license for passenger vehicles, while 16.2% have a driver's license for trucks. The remaining 11.2% of respondents either hold restricted licenses applicable to motorcycles or agricultural machinery or have no valid driving license at the time of the study. In terms of driving experience, 28.2% of respondents have held a driver's license for more than 10 years, 19.7% for 5 to 10 years, and 21.4% for 3 to 5 years. Additionally, 19.5% reported having less than 3 years of driving experience, while 11.2% did not possess a valid driver's license at the time of the study. The largest percentage of respondents, 66.7%, reported participating in traffic daily as motor vehicle drivers. An additional 20.5% stated that they participate occasionally as motor vehicle drivers. Furthermore, 12.8% reported being regular traffic participants, but not as drivers of motor vehicles (for example, as passengers, cyclists, or users of public transport). Additionally, 38.8% of all respondents reported occasionally driving a tractor, and among them, 11.1% do so on a daily basis, while the rest operate tractors less frequently. Conversely, 61.2% of respondents reported that they rarely or never drive a tractor.

4.2. Tractor Speed Estimate

Table 2 presents the descriptive statistics of the estimated tractor speed across all described conditions and tested speeds. The column labeled t refers to the t-value obtained from the one-sample t-test, while p denotes the p-value indicating the level of statistical significance for each tested condition.

In all tested conditions and speeds, respondents tended to overestimate the tractor's speed (Figures 4 and 5). Figure 4 illustrates the mean estimated speed across all six visibility configurations at the actual speed of 10 km/h. It can be observed that the presence of any visibility aid (SMV emblem, DRLs, or beacon light) consistently reduced the degree of overestimation compared to the no-equipment condition. The lowest estimation error occurred when only the SMV emblem was installed, while the absence of any visibility equipment led to the most pronounced overestimation.

Table 2. Descriptive statistics and analysis of the tractor speed estimation at all tested conditions and speeds.

Speed	Conditions	Mean	Str. Deviation	t	*p*
10 km/h	SMV emblem	14.30	9.00	17.18	0.000
	Lights	14.32	8.21	18.87	0.000
	Beacon light	14.82	9.47	16.92	0.000
	Beacon light and SMV emblem	14.74	10.11	15.77	0.000
	Everything from the equipment	14.54	10.41	15.10	0.000
	None of the equipment	15.21	10.08	16.32	0.000
20 km/h	SMV emblem	24.03	11.46	22.69	0.000
	Lights	23.54	11.48	22.17	0.000
20 km/h	Beacon light	25.15	11.01	24.72	0.000
	Beacon light and SMV emblem	24.88	10.34	26.04	0.000
	Everything from the equipment	22.42	10.22	23.74	0.000
	None of the equipment	24.19	11.52	22.72	0.000

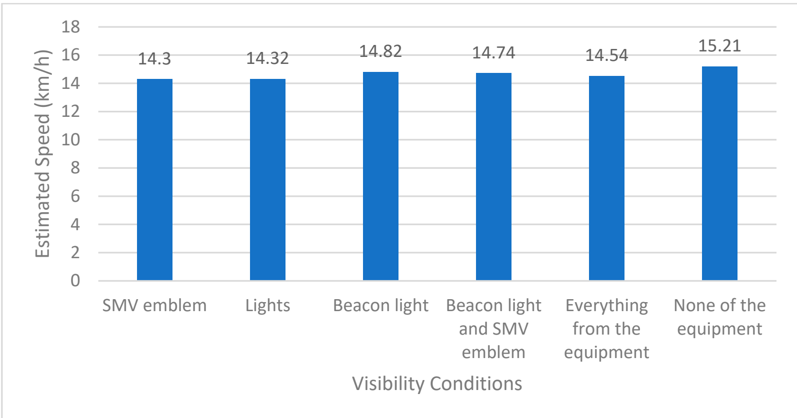

Figure 4. Descriptive statistics of the tractor's speed estimation under all tested conditions at a speed of 10 km/h.

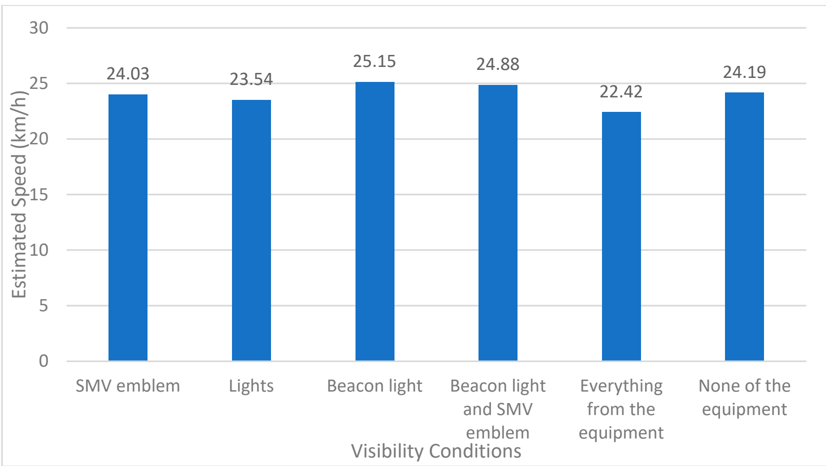

Figure 5. Descriptive statistics of the tractor's speed estimation under all tested conditions at a speed of 20 km/h.

Figure 5 presents the same pattern at the actual speed of 20 km/h. Notably, the configuration with all three visibility aids (DRLs, beacon light, and SMV emblem) resulted in the most accurate perception, with a mean estimated speed of 22.42 km/h. The largest overestimation was recorded when only the beacon light was active or when no equipment was installed, both resulting in perceived speeds exceeding 25 km/h.

Figure 6 provides a comparative overview of the average absolute estimation errors across all visibility conditions and speed levels. It clearly shows that combined visibility configurations generally yield smaller perceptual errors. The data suggest that the addition of even a single visibility feature improves perceptual accuracy, while the simultaneous use of all three yields the best results. This supports the conclusion that multi-modal visibility enhancements can significantly improve drivers' estimation performance and thus promote safer interactions.

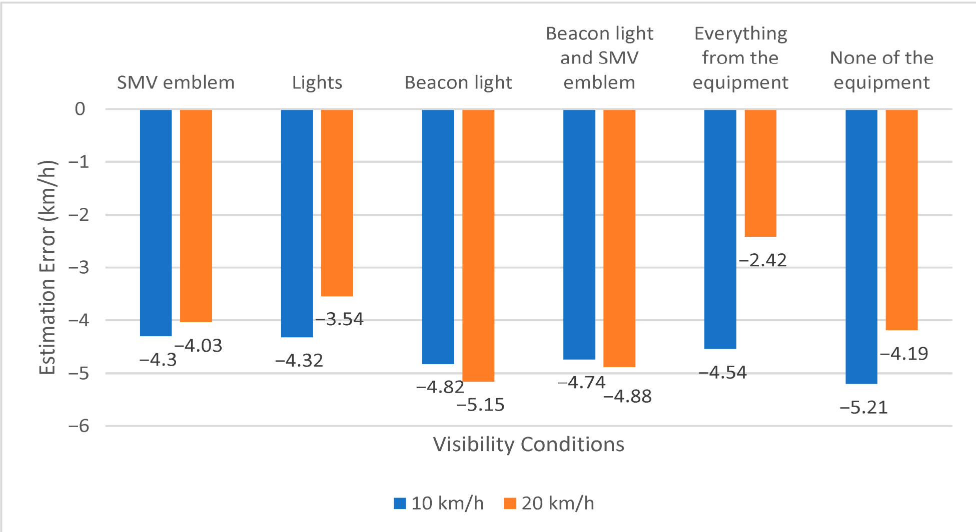

Figure 6. The average error in tractor speed estimation across all speeds and conditions.

In the condition where the tractor's daytime running light and beacon light were on, along with the SMV emblem installed, respondents estimated a speed of 20 km/h with the smallest error (M = 22.42; SD = 10.22). Meanwhile, the speed of 10 km/h was estimated with the smallest error when only the SMV emblem was installed on the tractor (M = 14.30; SD = 9.00). With the largest error, the respondents estimated the speed of 10 km/h in a situation when there was no equipment on the tractor (M = 15.21; SD = 10.08), while they estimated the speed of 20 km/h with the largest error when there was no equipment on and when the beacon light was on (M = 25.15; SD = 11.01).

The one sample test results indicate a statistically significant difference for all tested speeds and conditions, as shown in Table 2 (Hypothesis 1).

4.3. Gender Differences in Tractor Speed Estimation

The independent samples *t*-test was conducted to analyze differences in tractor speed estimation based on the respondents' gender (Hypothesis 2). The results (Table 3) reveal statistically significant differences for all tested speeds and conditions. In Table 3, the column labeled t refers to the t-value derived from the independent samples *t*-test, while *p* indicates the *p*-value representing the probability of obtaining the observed difference by chance.

Table 3. The relationship between the tractor speed estimation for all the tested speeds, for all tested conditions, and half of the respondents.

Speed	Conditions	Gender	Mean	Std. Deviation	t	p	Eta Square	Magnitude of Impacts
10 km/h	SMV emblem Lights	Man	11.687	5.721	−3.525	0.001	0.097	Large
		Woman	17.800	11.223				
	Beacon light	Man	11.701	5.681	−3.980	0.000	0.121	Large
		Woman	17.820	9.701				
	SMV emblem Lights	Man	11.836	6.273	−3.900	0.000	0.117	Large
		Woman	18.820	11.444				
	Beacon light	Man	12.030	8.730	−3.407	0.001	0.091	Large
		Woman	18.360	10.757				
	Everything from the equipment	Man	11.761	7.768	−3.284	0.002	0.086	Large
		Woman	18.260	12.279				
	None of the equipment	Man	12.687	7.097	−3.024	0.003	0.074	Moderate
		Woman	18.580	12.342				
20 km/h	SMV emblem Lights	Man	21.537	8.418	−2.622	0.011	0.056	Moderate
		Woman	27.380	13.975				
	Beacon light	Man	21.104	9.154	−2.584	0.012	0.054	Moderate
		Woman	26.800	13.430				
	SMV emblem Lights	Man	21.940	8.978	−3.711	0.000	0.107	Large
		Woman	29.460	12.048				
	Beacon light	Man	21.896	7.945	−3.617	0.001	0.102	Large
		Woman	28.880	11.804				
	Everything from the equipment	Man	19.851	8.576	−3.152	0.002	0.079	Moderate
		Woman	25.860	11.265				
	None of the equipment	Man	21.731	9.398	−2.615	0.011	0.056	Moderate
		Woman	27.480	13.253				

4.4. The Respondent's Place of Residence and Tractor Speed Estimation

The analysis of variance (ANOVA) revealed statistically significant differences in speed estimation accuracy depending on the respondents' place of residence, particularly in the scenario involving a tractor traveling at 10 km/h with only the SMV emblem installed (F = 2.581; $p = 0.041$). Participants residing in rural areas and small towns provided the most accurate estimations, with mean values closest to the actual speed, and the lowest standard deviations. This likely reflects their frequent exposure to slow-moving agricultural vehicles and more intuitive understanding of their movement. In contrast, respondents from urban environments, especially those living in the city center and inner-city areas, exhibited a clear tendency to overestimate tractor speed, with higher average values and greater variability. These findings emphasize the role of environmental familiarity in the development of accurate perceptual models, suggesting that limited real-life interaction with tractors in high-density urban zones may impair estimation accuracy.

4.5. Driving License Category and Tractor Speed Estimation

Statistically significant differences were also observed across all tested visibility conditions when respondents were grouped according to driving license category. Truck drivers consistently demonstrated the highest accuracy in estimating tractor speed at both 10 km/h and 20 km/h, regardless of the installed visibility equipment. Their estimations were closest to the true values, with low variability, indicating a stable and calibrated perceptual response, likely developed through regular professional interaction with large and slow-moving vehicles.

Passenger car drivers showed moderate accuracy overall but were notably less precise than truck drivers, particularly in conditions with no visibility aids or only partial equipment. Respondents without a driving license, as well as those currently in the process of training at a driving school, showed a consistent pattern of overestimation, with the most extreme deviations observed in conditions involving beacon lights or minimal signaling. This group also displayed wide standard deviations, indicating inconsistency in perceptual judgment.

A particularly concerning result emerged for motorcycle license holders, albeit a small subsample, who drastically overestimated speed in nearly all scenarios—sometimes by two to three times the actual value. Their responses suggest a perceptual bias possibly linked to limited exposure to slow-moving vehicles or differing spatial heuristics acquired through motorcycle operation.

Overall, these findings highlight that the category of driving license is a strong predictor of perceptual performance, with professional experience (e.g., truck driving) correlating with lower estimation error. This suggests that the perceptual calibration gained through regular exposure to large vehicles can significantly improve judgment accuracy. The results also underscore the need to reinforce perception-related training—especially concerning agricultural vehicles—in driver education programs across all license categories, including novice drivers and those with limited driving experience.

4.6. Years of Possession of the Driver's License and Tractor Speed Estimation

One-way ANOVA was used to analyze differences in tractor speed estimation based on the years of driver's license ownership (Hypothesis 5). The results show no statistically significant differences in tractor speed perception, regardless of the years of license ownership, for all tested speeds and conditions.

4.7. Frequency of Driving a Motor Vehicle and Tractor Speed Estimation

One-way ANOVA was used to analyze the relationship between the frequency of driving a motor vehicle (daily, less than 3 times a week, 3 to 5 times a week, less than 3 times a month, and less than three times a year) and tractor speed estimation (Hypothesis 6). The results show significant statistical differences in the estimation of 10 km/h with the tractor's daytime running lights on (F = 2.560; p = 0.031), 20 km/h with the SMV emblem installed (F = 2.394; p = 0.042), and 20 km/h with both the beacon light and SMV emblem installed (F = 3.112; p = 0.011).

Respondents who drive a vehicle 3 to 5 times a week provided the most accurate estimates with the smallest error when estimating the tractor's speed at 10 km/h with the tractor's daytime running lights on (M = 10.00; SD = 5.873), as well as when estimating the tractor's speed at 20 km/h with the SMV emblem installed (M = 16.00; SD = 6.633). For estimating the speed of 20 km/h in the condition where both the beacon light and SMV emblem were installed on the tractor, the most accurate estimate (smallest error) was provided by respondents who drive a motor vehicle less than 3 times a year (M = 16.667; SD = 7.637).

4.8. Impact of Tractor Driving Experience on Tractor Speed Estimation

The relationship between the frequency of tractor driving and the accuracy of tractor speed estimation was first examined using a one-way ANOVA. The results indicated no statistically significant differences across all tested speeds and visibility conditions, suggesting that how often a respondent drives a tractor does not substantially influence their ability to estimate its speed.

However, a more pronounced effect was observed when comparing respondents who reported driving a tractor in traffic with those who do not. An independent samples *t*-test revealed statistically significant differences in speed estimation for all tested speeds and conditions. Across nearly all scenarios, respondents with actual experience operating tractors in traffic consistently demonstrated lower estimation errors compared to those without such experience. These differences were particularly notable in configurations where visibility equipment was either partially present or completely absent.

The largest perceptual gap was observed in the condition with only the beacon light activated at 20 km/h, where drivers without tractor experience overestimated the speed to a significantly greater extent than those who regularly operate tractors. Effect size analyses confirmed that these differences ranged from small to large, depending on the specific visibility configuration, with the strongest effects appearing at higher speeds and in conditions involving incomplete or minimal visibility equipment.

These findings underscore the importance of practical exposure to slow-moving agricultural vehicles in developing accurate perceptual judgments. Familiarity with the operational dynamics and typical appearance of tractors under real traffic conditions appears to contribute significantly to more accurate estimation of their speed, which in turn has direct implications for overtaking behavior and overall traffic safety.

4.9. The Relationship Between Road Crashes and Tractor Speed Estimation

The potential connection between respondents' participation in road crashes and tractor speed estimation was examined using the independent samples *t*-test (Hypothesis 8). The results show statistically significant differences in the estimation of tractor speed at 10 km/h when the tractor has its daytime running light, beacon light, and SMV emblem installed ($F = -2.031$; $p = 0.045$).

4.10. Cluster Analysis of Drivers Based on Speed Perception Patterns

To further explore the variability in drivers' speed estimation accuracy, a cluster analysis was performed using k-means clustering. This unsupervised machine learning technique was applied to identify distinct subgroups among the respondents based on both their demographic attributes and behavioral patterns in speed estimation. Variables included in the clustering model were gender, age, place of residence, driving license category, frequency of general vehicle use, frequency of tractor use, and average estimation error across the 12 visibility conditions. Prior to clustering, all variables were normalized to ensure comparability. The optimal number of clusters was determined using the Elbow Method, which suggested a three-cluster solution.

Cluster 1 ("Experienced Rural Estimators") consisted predominantly of older, rural-based respondents with frequent exposure to tractors. This group exhibited the lowest average error in speed estimation, particularly in scenarios involving visibility equipment.

Cluster 2 ("Urban Overestimators") was characterized by younger drivers living in urban areas, most of whom reported limited contact with tractors. They showed consistently higher estimation errors, especially in low-visibility conditions.

Cluster 3 ("Mixed Experience Respondents") included participants from various environments and driving experience levels. Their estimation errors varied considerably across visibility conditions, indicating a lack of consistent estimation patterns.

A one-way ANOVA confirmed significant differences between clusters in average estimation error ($F = 6.41$; $p < 0.01$). Post hoc analysis using Tukey's HSD test indicated that Cluster 1 had significantly lower errors than Cluster 2 ($p < 0.01$), while differences between Clusters 1 and 3 and Clusters 2 and 3 were marginally significant.

These findings suggest that perception accuracy is not solely determined by individual factors, such as gender or license type, but emerges from a combination of demographic and behavioral characteristics. The results further highlight the potential value of tailored safety campaigns, particularly aimed at urban drivers who are less familiar with slow-moving agricultural vehicles.

5. Discussion

The research that was conducted has significant implications for understanding the impact of vehicle visibility equipment on the safety of all road users, especially tractor drivers. The results point to several key conclusions that can contribute to the improvement of road safety and adjust the legal regulations. This discussion highlights several key aspects based on the results obtained.

The data on the number of road crashes [32,33,35,47] with tractors in Serbia emphasize the seriousness of the safety challenges that these vehicles represent. Especially since tractors account for about 1.4% of all road crashes, with a significant number of deaths and injuries [31]. This raises the question of the effectiveness of current safety measures and the need for further innovation. Based on the results obtained and presented in the paper, it can be concluded that vehicle visibility equipment significantly contributes to a better perception of the tractor's speed and thereby improves the tractor's active safety. It should be emphasized that the use of only a beacon light is not sufficient for the accurate perception of the tractor speed. The perception of the tractor, as well as the accuracy of the estimation of the tractor's speed, has a great influence on the occurrence and severity of the consequences of road crashes involving tractors.

An analysis of the types of road crashes, especially collisions with the rear and front of tractors, as well as with trailers, provides additional information on the risks [8,31,71–76]. This type of road crash most often occurs outside the settlement. The mentioned fact only confirms the results obtained and shown in the paper about the importance of the perception of the tractor's speed. The accuracy of the perception of tractor speed is also influenced by the demographic characteristics of the respondents (gender, place of residence, frequency of driving, driver's license category). While for a detailed explanation of the existence of gender differences in the perception of tractor speed, additional research must be done (primarily a personality test and other tests on male and female subjects, other differences can be explained more easily. The place of residence has an influence on the accuracy of the estimation of tractor speed, so that respondents from rural areas, who encounter tractors more often (or can operate a tractor more often), have a more accurate estimation of tractor speed, in contrast to respondents from urban areas. The frequency of driving [4,57,77,78] also influences the accuracy of the estimation of the tractor's speed, so drivers with more experience have a more accurate estimation of the tractor's speed. These findings indicate the importance of experience for the accuracy of the estimation of tractor speed. On the other hand, the driver's license category has an impact on the accuracy of the tractor speed estimate. Like experience, this finding only indicates the importance of experience for the accuracy of tractor speed estimation. The above facts should be used to create an educational program [4,77,78] in driving schools, but also in other ways (campaigns on traffic, school competitions, tribunes, etc.), in order to draw attention to the importance of using vehicle visibility equipment for the accuracy of estimating tractor speed, but also the importance of other factors for the improvement of all road users. Also, the importance of the data obtained and presented and analyzed in the work should also be a task for the well-founded and science-based attitudes of the state legislative authority for the creation of legal solutions regarding tractor drivers [79,80].

The results of the cluster analysis provide an important extension to the previously reported findings, offering a more nuanced understanding of how various driver profiles relate to perceptual accuracy. The identification of the "Experienced Rural Estimators" cluster, with significantly lower estimation errors, reinforces the idea that both exposure to agricultural traffic and routine familiarity with tractors contribute to more accurate speed judgments. In contrast, the "Urban Overestimators" cluster illustrates a clear vulnerability among drivers with limited interaction with tractors, who consistently overestimated speed—especially in scenarios lacking visibility aids. These insights suggest that perceptual biases are not uniformly distributed across the driver population but instead follow patterns shaped by contextual and experiential factors. From a policy and education standpoint, these findings underscore the importance of targeted interventions—such as simulator-based training or awareness campaigns—focused on urban and less-experienced drivers, who may benefit most from increased exposure to realistic scenarios involving slow-moving agricultural vehicles.

Beyond academic relevance, the findings of this study have important practical implications for traffic safety policy, vehicle design, and educational initiatives. For example, the demonstrated impact of specific visibility equipment configurations on perceptual accuracy can inform legislation mandating the use of DRLs and SMV emblems on agricultural vehicles. In addition, the results may be used to improve driver education curricula, particularly by integrating simulator-based training to help urban drivers better estimate the speed of slow-moving vehicles. The findings can also guide manufacturers in designing more conspicuous lighting and signaling systems for tractors and similar vehicles operating on public roads.

Limitations and Future Research

Despite the methodological rigor of this study, several limitations should be acknowledged. First, the use of a driving simulator, although effective for experimental control, may not fully replicate the complexity of real-world driving, particularly under dynamic environmental conditions (e.g., variable lighting, weather, or road distractions). Second, the study focused on a specific tractor model and two selected speeds, which may limit the generalizability of findings to other types of agricultural vehicles or higher-speed contexts. Third, the sample consisted of participants from one country, and cultural or regional familiarity with agricultural traffic might influence perceptual accuracy. Additionally, while this study analyzed some demographic influences, such as gender and residence, it did not explore deeper psychological or cognitive variables (e.g., risk perception, attention span, or personality traits), which may also play a role in speed estimation. Future research should expand to include more diverse vehicle types, broader speed ranges, and real-world conditions, as well as a more comprehensive psychological profiling of drivers [28,81,82].

6. Conclusions

The findings of this study confirm that the perception of tractor speed is significantly influenced by the presence and configuration of vehicle visibility equipment. The most accurate estimations occurred when tractors were equipped with a full set of visibility aids, including daytime running lights, beacon lights, and the SMV emblem, particularly at higher operational speeds. Conversely, the absence of such equipment led to a notable increase in perceptual error, emphasizing the crucial role of visual cues in enhancing driver awareness and response. Beyond the equipment itself, individual differences among drivers, shaped by gender, place of residence, driving habits, and license category, further contributed to variability in speed perception. These differences were particularly evident among respondents from urban environments and those with limited exposure to agricultural vehicles, who demonstrated a tendency toward overestimation. Notably, the frequency of general vehicle use, rather than tractor-specific experience, emerged as a more consistent predictor of estimation accuracy. While some factors, such as years of license possession or frequency of tractor driving, did not show a statistically significant influence, others, such as crash involvement history, proved relevant under specific conditions, highlighting the multifaceted nature of perceptual performance in traffic contexts.

The inclusion of cluster analysis in this study significantly enhanced the understanding of individual differences in speed perception related to tractor visibility. By identifying distinct driver profiles based on demographic and behavioral attributes, the analysis demonstrated that estimation accuracy is not uniformly distributed across the population. Instead, it is shaped by factors, such as driving experience, place of residence, and frequency of interaction with agricultural vehicles. These findings provide a solid basis for the development of more effective, evidence-based road safety strategies tailored to the needs of specific driver groups. Incorporating this knowledge into educational programs and legislative planning may contribute to a more inclusive and efficient approach to enhancing rural traffic safety and promoting sustainable mobility.

Overall, the study offers empirically grounded insights into how low-cost visibility measures can reduce perceptual errors and improve the active safety of tractors in rural road environments. These conclusions are especially relevant for safety policies involving slow-moving agricultural vehicles. As such, the practical application of these findings supports the development of targeted educational interventions, especially for urban drivers, and encourages the integration of visibility standards into national traffic safety regulations. The results may also serve as a foundation for future revisions to road traffic legislation, aimed at standardizing the use of visual warning systems on slow-moving vehicles.

Future research should build on these insights by examining a broader range of visibility technologies and their interaction with human cognitive factors. Potential directions include the integration of smart lighting systems, real-time warning interfaces, and adaptive perception-based technologies. Moreover, cross-cultural comparisons could shed light on perceptual and behavioral variations in international contexts, contributing to the development of harmonized global safety standards. In parallel, interdisciplinary studies that combine psychological profiling, risk perception analysis, and neurocognitive testing would offer a deeper understanding of the mechanisms underlying speed misjudgment. Altogether, this research paves the way toward a safer, more perceptually aligned traffic system, particularly in agricultural and mixed rural environments.

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